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Interactive Value Model Trading for Resilient Systems Decisions

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Abstract

With the rise of readily accessible computation and data storage capabilities, models have been increasingly leveraged for generating system data to support decision making. Moving beyond considerations of what makes a good model, Interactive Model-Centric Systems Engineering seeks to address core challenges as well as key implications associated with relying upon models for generating the data upon which important system decisions are made. Among these is the issue of understanding the consequences of model choice itself. This paper proposes three categories of models: performance, cost, and value, and addresses the question of value model trading. The concept is illustrated through a demonstration Space Tug satellite system case where four value models (multi-attribute utility, analytic hierarchy process, cost-benefit analysis, and measure of effectiveness) are each used to assess the goodness of potential system alternatives. The consequence of value model choice changes the Pareto efficient set of "best" system solutions, and a comparison of these sets reveals the potential of finding system solutions that are robust to value model choice, supporting the strategic goal of identifying resilient system decisions.

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Keywords: value models; multi-attribute utility; analytic hierarchy process; cost-benefit analysis; measure of effectiveness; robust solutions; tradespace exploration; resilience

1. Introduction

As evidenced by the recent rise of model-influenced systems engineering efforts, including Model-Based Systems Engineering, Model-Based Engineering, and Interactive Model-Centric Systems Engineering, the role of models in engineering activities has been increasing in scope[1]. Models have always been used as tools to augment human ability to make predictions or sense of information, encapsulating existing knowledge, as well as automating

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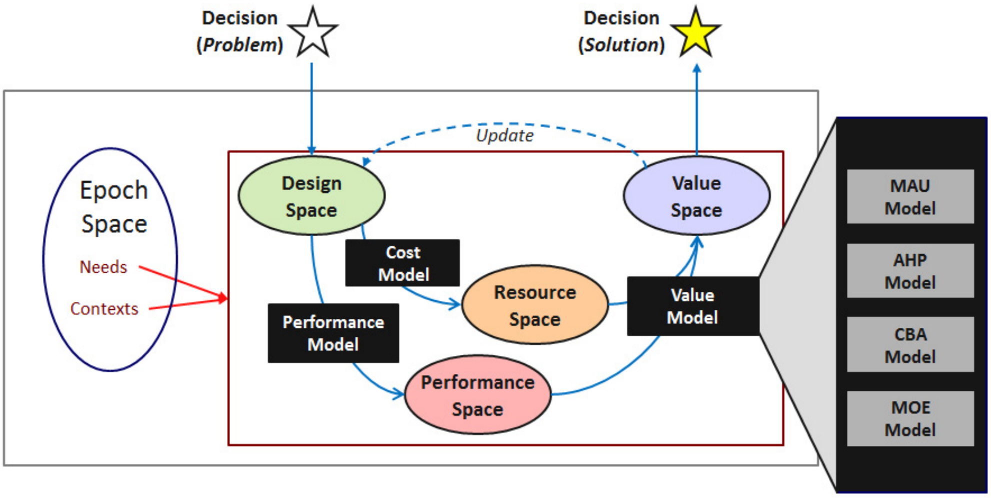


Fig. 1. Role of key models for supporting system decision making, with alternative value models used in demonstration case.

its application. The rapid rise of low expense computational ability has increased the accessibility of numerical models and the roles they can play in engineering, including both analysis and synthesis. Leveraging models in an effective way for engineering decision support necessitates understanding the role that model choice plays in the generation and analysis of data for decision making. This is especially true when seeking to identify system solutions in early design that are robust across uncertainties[2]. This paper reports on preliminary research in helping to frame this challenge and potential insights that might be gained when actively trading models as a part of a study.

1.1. Motivation/Background

There are several key concepts involved during design decision making in early phase design. Fig. 1 depicts the general relationship between decision problems and decision solutions as they relate to data and models in early phase engineering analysis. In this figure, decision problems suggest a space of potential solutions, which span a design space. The design space is then sampled and evaluated through two types of models: cost models and performance models. Cost models seek to predict the resources needed to develop and operate each of the evaluated potential systems. Typically these estimates are in terms of dollars, and potentially time (i.e. schedule). Performance models seek to predict the operational behavior in context of the evaluated potential systems. Value models seek to map the resulting resource and performance predictions into decision-friendly perceived benefit and cost metrics. Value models can be simple (e.g., just the cost and performance measures), or complex (e.g. aggregate perceived benefit and cost under uncertainty of a large number of measures), with many possible implementations[3]. Each of these models, and the artificial data generated by them, can be potentially altered by changes in the epoch space (i.e., exogenous context and needs changes). Updating occurs when users seek to modify the space definitions, or the models, in order for them to better address the problem under consideration (or to improve the trust or truthfulness (i.e., validity) of the models and data).

Since the role of models is central in the depicted decision framework, it is essential that engineers and analysts understand not only the sensitivities of their proposed solutions, but also of the models from which the data for decisions are generated. This includes understanding the impacts of key assumptions and model formulations on the data. One means for conducting this investigation is through “model trading” (i.e., model selection) where data is generated using alternative models with the resulting data compared.

In this research, the team has begun exploratory work defining model types and formulation of how model trading might be implemented. Leveraging insights from earlier work[4], which described the role of interactivity in refining a user’s captured value model, we generalize the concept as “value model trading.” This ranges from tuning parameters within a particular value model (e.g., utility function shapes and weights for a Multi-Attribute Utility value model) to also include trading of value model formulations themselves[1]. There are many possible value models[5]. For this paper demonstration, four alternative value model formulations were used: Multi-Attribute Utility (MAU), Analytic Hierarchy Process (AHP), Cost-Benefit Analysis (CBA), and Measure of Effectiveness (MOE) (see Fig. 1). Recall, a value model attempts to predict how a particular decision maker might perceive net benefits and costs for alternatives under consideration. Different value models treat the mapping of raw data to perceived benefits and costs differently. For illustration purposes, we treated perceived costs as just lifecycle cost (essentially as a single dimensional metric of perceived cost), while we varied the perceived benefit model across MAU, AHP, CBA, and MOE. The results of this variation were analyzed in terms of how the set of perceived benefit versus cost efficiency changed. This was calculated as the Pareto efficient set (i.e., non-dominated solutions across the two high level objectives) for the given value models. The sets were then compared to see the impact of value model choice on proposed "best" alternative solutions. This demonstration case utilized the IVTea Suite software being developed internally at MIT to support value-driven tradespace exploration and analysis.

2. Demonstration of value model trading: space tug

For this exploratory case, the problem is framed as the following:

> A decision maker has a budget for an orbital transfer vehicle (a.k.a. "Space Tug") and thinks he knows what he wants (in terms of attributes of goodness of a system). But he is aware that he may not have formulated his value model correctly. He wants to explore three types of uncertainties in his value model:
>
> 1. What value model best represents his preferences?
> 2. What parameters for a given value model best represent his preferences?
> 3. What if he really doesn't know what his true preferences are and wants instead a robust solution?

The second question was previously addressed[4], while the first and third questions are investigated in this paper. The approach in this study is to use four different value models to evaluate and represent benefit vs. cost tradeoffs; identify the most value efficient alternatives under different value models; compare preferred alternatives across value models; and find solutions that perform well across the alternative value models.

2.1. Models used in the case

The design alternatives and performance and cost models for Space Tug are relatively straightforward, consisting of the rocket equation and some linear relationships[6]. The value models used in this study are now described:

2.1.1. Multi-attribute utility (MAU)

Multi-Attribute Utility value model generates an aggregate measure across multiple criteria (called attributes)[7]. Each of the attributes have single attribute utility functions that map attribute level to perceived benefit under uncertainty of that attribute (typically quantified on a zero to one scale). The set of single attribute utility functions is then aggregated via a multi-linear function into a multi-attribute utility score. The equation for MAU is:

$$U(\hat{X}) = \frac{\left[\prod_{i=1}^{n}(K \cdot k_i \cdot U_i(X_i)+1)\right]-1}{K},\ where\ K = -1 + \prod_{i=1}^{n}(K \cdot k_i + 1)$$

Here K is the normalization constant, $U(\hat{X})$ is the aggregate MAU value across the multiple single attributes X_i and their respective single attribute utilities $U_i(X_i)$; k_i is the elicited swing weighting factor for attribute X_i; n is the number of attributes. Fig. 2 illustrates the three single attribute utility functions (i.e., capability, delta V, response time), along with their k_i weights for the MAU function. In the special case where the weights add to 1, the function becomes a linear weighted sum, and therefore each attribute contributes independently to the aggregate value.

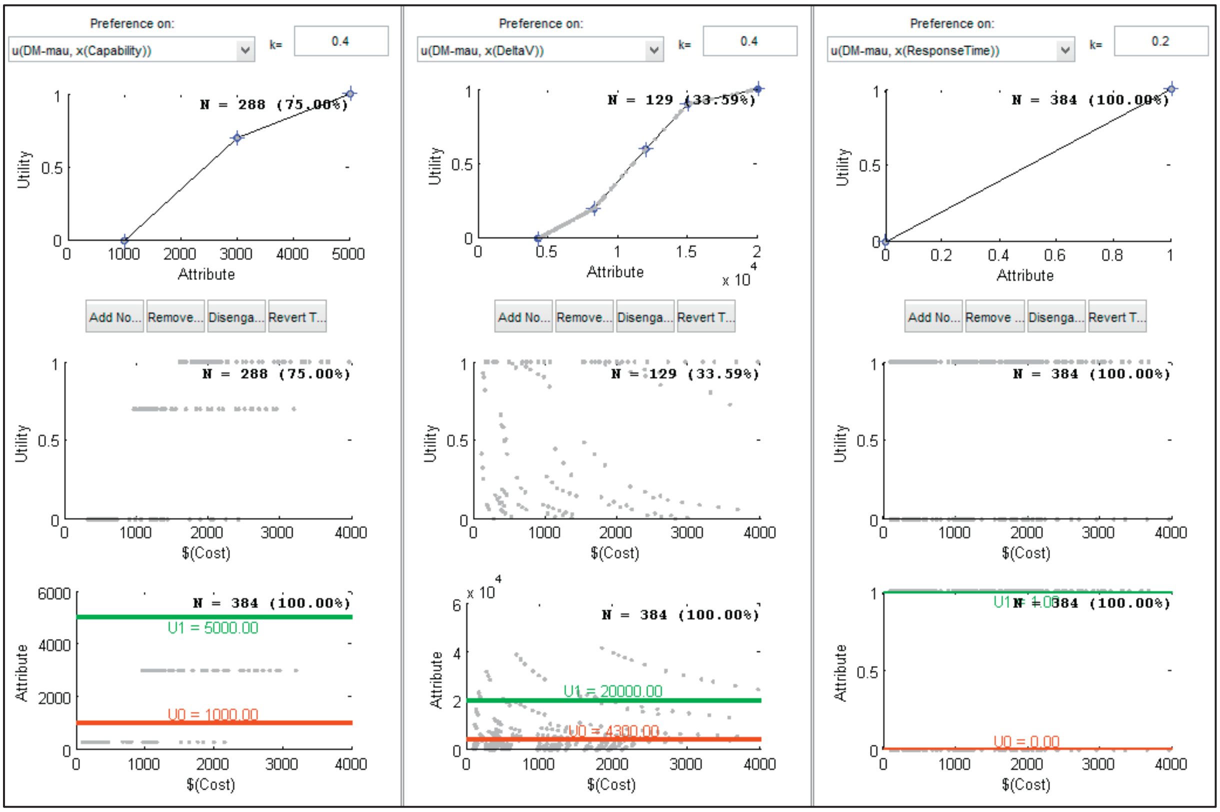


Fig. 2. Single attribute utility functions for the MAU value model.

Each of the Space Tug design alternatives were then evaluated in terms of the MAU benefit and cost and are plotted in Fig. 4a below. Additionally, the Pareto efficient set of designs, which are the most benefit-cost efficient solutions, non-dominated in this two objective space, are indicated with blue triangles (flat side on bottom). Due to the nature of MAU, design alternatives that do not meet minimum acceptable levels in any particular attribute are deemed unacceptable and are treated as infeasible. This results in a smaller set of designs to consider (here as N=83, out of the total possible of 384). The designs in the Pareto set did not share many common features, but all had propulsion systems that were electric (type 3) or nuclear (type 4).

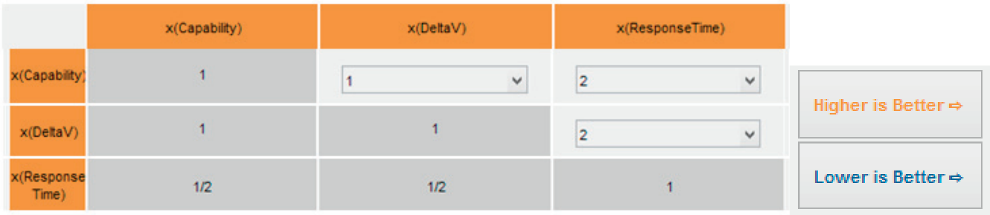
2.1.2. Analytic hierarchy process (AHP)

Analytic Hierarchy Process value model generates an aggregate measure across multiple criteria[8]. Each of the criteria are evaluated pair-wise to determine relative value contribution. The aggregate AHP score is determined using a linear-weighted sum, with the weights derived from the pairwise comparisons. The AHP value equation is:

$$AHP(\hat{X}) = \sum_{i=1}^{n} k_i \cdot AHP_i(X_i), \text{ where}$$

$$AHP_i(X_i) = \frac{(X_i - X_{i,min})}{X_{i,max} - X_{i,min}}, \text{ if bigger is better for } X_i; \text{ or } AHP_i(X_i) = \frac{(X_{i,max} - X_i)}{X_{i,max} - X_{i,min}}, \text{ if smaller is better for } X_i,$$

$$k_i = \frac{\sum_{q=1}^{n} \frac{a_{i,q}}{\sum_{p=1}^{n} a_{p,q}}}{n}, \text{ where } a_{pq} \text{ is the element in row } p, \text{ column } q \text{ in the AHP matrix, } n \text{ is the number of criteria.}$$



	x(Capability)	x(DeltaV)	x(ResponseTime)
x(Capability)	1	1	2
x(DeltaV)	1	1	2
x(Response Time)	1/2	1/2	1

Fig. 3. Matrix of comparisons for the AHP value model.

Fig. 3 illustrates the pair-wise comparison matrix for the three criteria (capability, delta V, and response time), which resulted in calculated k_i weights of 0.4, 0.4, and 0.2 respectively.

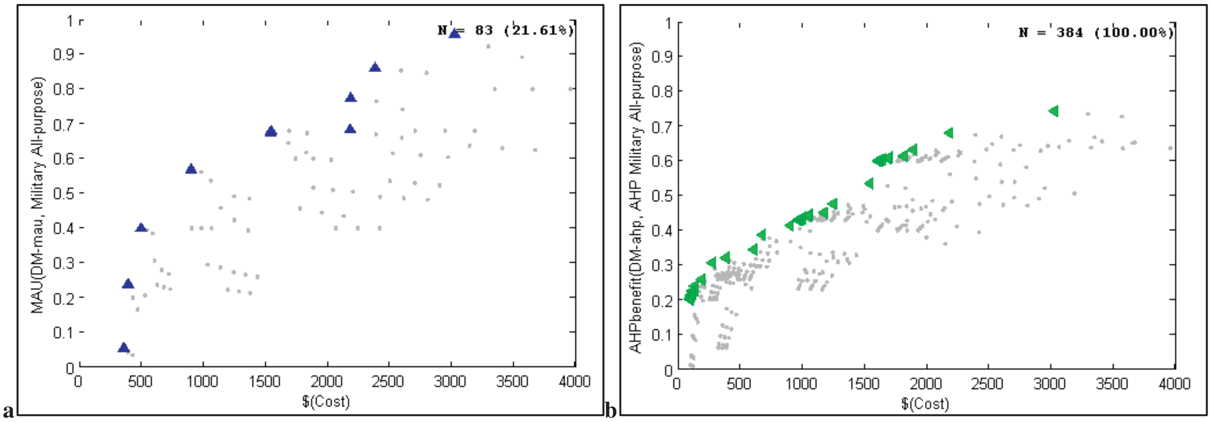


Fig. 4. (a) MAU benefit vs. cost tradespace; (b) AHP benefit vs. cost tradespace (with Pareto efficient sets indicated).

Each of the Space Tug design alternatives were then evaluated in terms of the AHP benefit and cost and are plotted in Fig. 4b Additionally, the Pareto efficient set of designs are indicated with green triangles (flat side on right). Due to the nature of AHP value, no design alternatives are rejected, so the full tradespace appears feasible (N=384). The designs in the Pareto set have no obvious pattern except they never have electric propulsion (type 3).

2.1.3. Cost-benefit analysis (CBA)

Cost-Benefit Analysis value model converts multiple criteria into a common currency (typically dollars) in order to simplify comparisons[9]. In order to construct this model, one must create monetization (conversion) functions for each of the criteria. For this case demonstration, each conversion function has three parameters, which assumes a minimum acceptable level (zero), a marginal dollar per unit of the attribute (the conversion rate), and (optionally) a diminishing returns rate (if the marginal rate decreases with an increase in attribute level). After calculating each individual criterion as a dollar figure, the aggregate is a simple sum of the three. The equation for CBA value is:

$$CBA(\hat{X}) = \sum_{i=1}^{n} CBA_i(X_i),$$

$$CBA_i(X_i) = \frac{m_i}{r_i}(1 - e^{-r_i \cdot X_i}),\ when\ X_i \geq X_{i,min};\ or\ CBA_i(X_i) = 0,\ \ when\ X_i < X_{i,min}$$

Where m_i is the marginal rate of dollars per unit attribute, r_i is the (optional) diminishing return rate, and X_{min} is the minimum acceptable level (or zero point) for bigger is better functions. When there is no diminishing returns rate, the CBA function is simply a linear function of (i.e., $Y = m_i X_i$.) Fig. 5 illustrates the three monetization functions for the three criteria (capability, delta V, and response time).

Fig. 5. Attribute monetization functions for the CBA value model.

Each of the Space Tug design alternatives were then evaluated in terms of the CBA benefit and cost, and are plotted in Fig. 6a below. Additionally, the Pareto efficient set of designs are indicated with red triangles (flat side on left). Due to the nature of CBA value no design alternatives are rejected, so the full tradespace appears feasible (N=384). The designs in the Pareto set tend to have small payloads and never have electric propulsion (type 3).

2.1.4. Measure of effectiveness (MOE)

Delta V was used as a single dimension Measure of Effectiveness[10] since it represents the fundamental capability for transferring target vehicles from one orbital slot to another. For clarity we use a single MOE, but one could use all three attributes, each as a measure of performance (MOP) and perform multi-dimensional Pareto analysis to identify the non-dominated solutions. Using a performance metric as the MOE might be considered equivalent to “not having a value model.” However, a value model is always being used when a study is synthesizing information to form the basis of a decision, even if a decision maker does not explicitly acknowledge a value model as such.

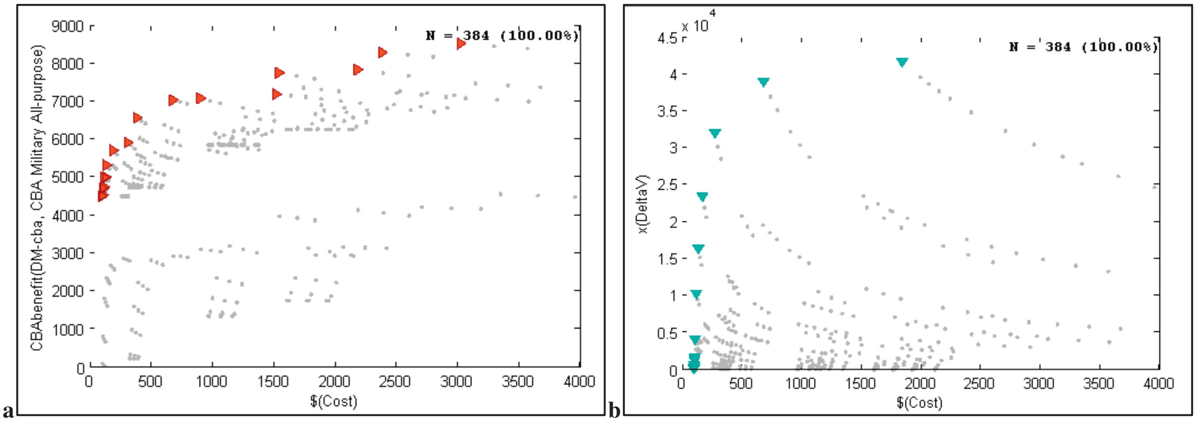


Fig. 6. (a) CBA benefit vs. cost tradespace; (b) MOE (Delta V) benefit vs. cost tradespace (with Pareto efficient sets indicated).

Each of the Space Tug design alternatives were evaluated in terms of the MOE benefit and cost and are plotted in Fig. 6b. Additionally, the Pareto efficient set of designs are indicated with cyan triangles (flat side on top). Due to the nature of MOE value, no design alternatives are rejected, so the full tradespace appears feasible (N=384). The designs in the Pareto set tend to have electric propulsion since this will result in the largest delta V for a given mass spacecraft. All of the designs also have the minimum size payload, which again reduces the overall dry mass of the spacecraft, resulting in additional delta V capability for the Space Tug to impart on target spacecraft.

3. Results

Now that each of the Space Tug designs have been evaluated with each of the value models and each suggests a particular set of value efficient designs, the next step is to compare Pareto sets across the four value models.

3.1. Comparisons via pareto sets

Fig. 7 illustrates the four perceived benefits versus costs tradespaces across the four value models, with all four Pareto sets indicated. Upon inspection, it appears that no single point appears in all four Pareto sets, but there are a few designs that appear in three out of four of the sets.

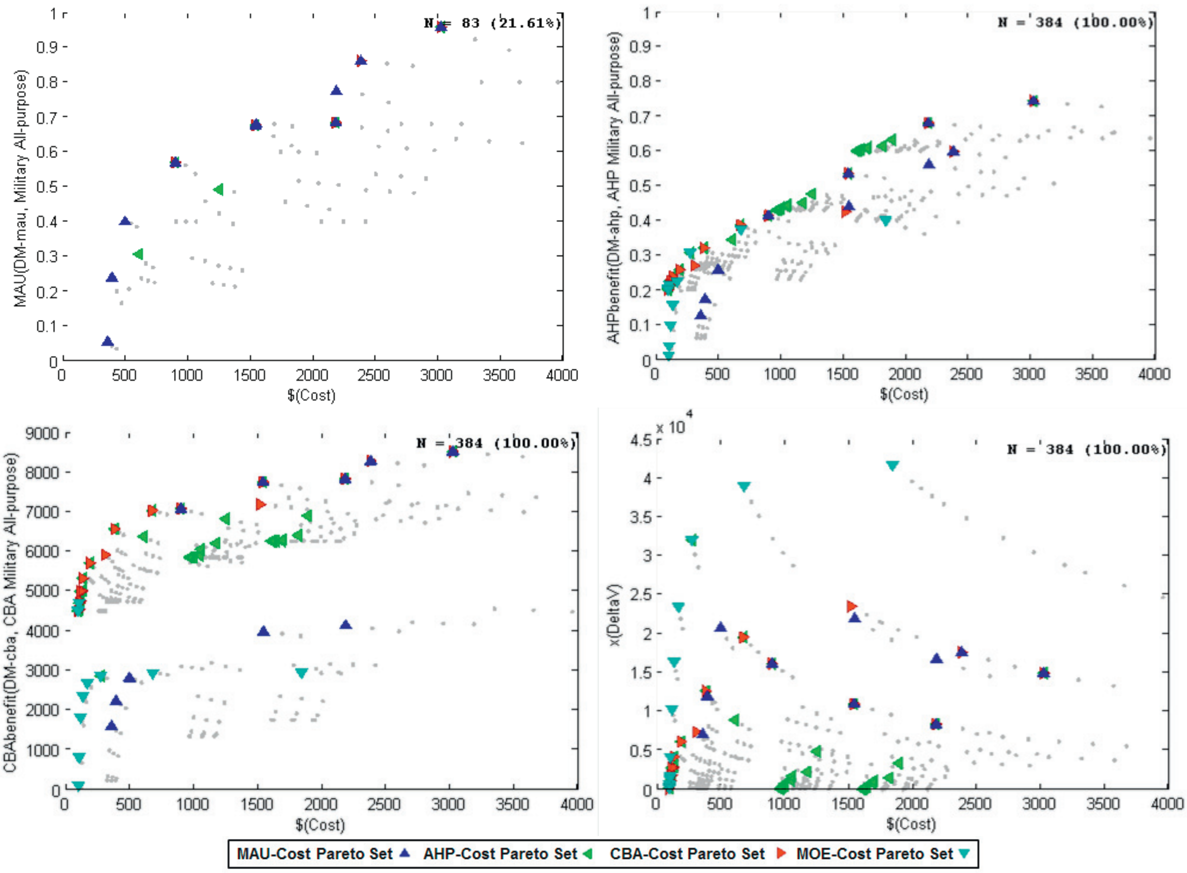


Fig. 7. Comparison of four value tradespaces.

The next step in the study is a more formal joint Pareto set analysis to determine the specifics of apparently attractive designs. This type of analysis uses standard multi-objective optimization techniques along with set theory and has been implemented within the IVTea Suite (MATLAB®-based) software mentioned earlier.

3.2. Joint pareto analysis

The joint Pareto analysis entails determining the Pareto set for each of the four pairs of objectives (i.e., benefit and cost functions for each of the four value models). The number of valid designs, along with each Pareto set size (indicated as "0% PARETO") is indicated in Fig. 8. It is important to notice that there are zero "joint" designs. Here, "joint" means that the design appears in all individual Pareto sets. Instead, there are six "compromise" designs, which are determined by calculating the Pareto set across the union of all objective functions. These represent efficient solutions that are non-dominated across the full set of objectives.

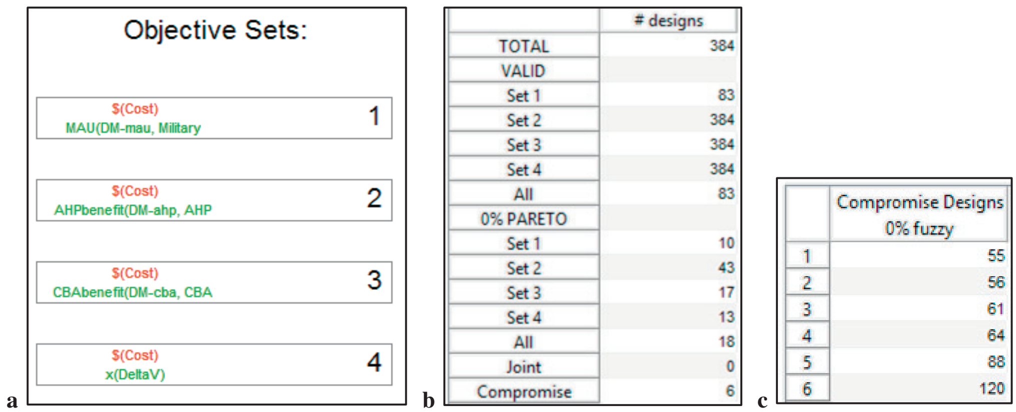


Fig. 8. Joint Pareto analysis with (a) four objective sets of two objectives each; (b) analysis results; (c) list of six compromise designs.

Upon closer inspection, we find that there are also six designs that are in three out of four Pareto sets. These are listed in Table 1, but two of the six are invalid for the MAU value model (meaning they do not provide minimum acceptable benefit in one or more attributes). These designed are considered "promising" if efficiency across three out of four value models is sufficient.

Table 1. Promising designs that are joint Pareto efficient across three out of four value models.

ID Number	Pareto Efficient For	Invalid For
1	2, 3, 4	1
11	2, 3, 4	1
63	1, 2, 3	
95	1, 2, 3	
127	1, 2, 3	
128	1, 2, 3	

The details of the promising designs are described in Fig. 9. If we do not consider designs 1 and 11, which are invalid for the MAU value model, we see a few common design choices among the remainder of the designs: they all use nuclear propulsion (type 4), and a large amount of fuel. Each of these four designs are highly attractive across the value models, and are most benefit-cost efficient for three out of four. These are, however, very expensive systems (as determined by the nuclear propulsion and large amount of fuel). Finding less expensive alternatives that are also robust to value model choice would be attractive at this point.

One other technique we can leverage in trying to find "robust" solutions that are insensitive to value model choice is to calculate fuzzy Pareto efficient sets[11]. We varied the fuzziness level and found that a single design does appear to be fully joint Pareto efficient at a fuzzy level of 7%. This means the design is within 7% of Pareto efficiency for all four value models. An additional attractive feature of this fuzzy Pareto design is its lower cost.

	1	11	63	95	127	128
$(Cost)	96.876	105.24	900	1540	2180	3020
$(Cost)	96.876	105.24	900	1540	2180	3020
$(Cost)	96.876	105.24	900	1540	2180	3020
$(Cost)	96.876	105.24	900	1540	2180	3020
$(Cost)	96.876	105.24	900	1540	2180	3020
dv(DesignforChange)	0	0	0	0	0	0
dv(DesignID)	1	11	63	95	127	128
dv(PayloadMass)	300	300	1000	3000	5000	5000
dv(PropMass)	30	300	10000	10000	10000	30000
dv(PropType)	1	2	4	4	4	4
x(Capability)	300	300	1000	3000	5000	5000
x(DeltaV)	142.608	1697.46	16149.6	10984.1	8387.01	14948.9
x(ResponseTime)	1	1	1	1	1	1
x(DeltaV)	142.608	1697.46	16149.6	10984.1	8387.01	14948.9
iv(BaseMass)	0	0	1000	1000	1000	1000
iv(DryMass)	603.6	639	5000	9000	13000	17000
iv(SpecificImpulse)	300	450	1500	1500	1500	1500
iv(MassFrac)	0.12	0.13	0.2	0.2	0.2	0.2
iv(WetMass)	633.6	939	15000	19000	23000	47000
MAU(DM-mau, Military All-purpose)	NaN	NaN	0.5692	0.67607	0.68376	0.95796
u(DM-mau, x(Capability))	NaN	NaN	0	0.7	1	1
u(DM-mau, x(DeltaV))	NaN	NaN	0.92299	0.49017	0.20941	0.89489
u(DM-mau, x(ResponseTime))	1	1	1	1	1	1
AHPbenefit(DM-ahp, AHP Military All-purpose)	0.20114	0.2161	0.4147	0.53522	0.68045	0.74358
CBAbenefit(DM-cba, CBA Military All-purpose)	4500	4702.108	7075.5553	7745.3006	7827.9318	8517.5532

Fig. 9. Details on the "promising" designs.

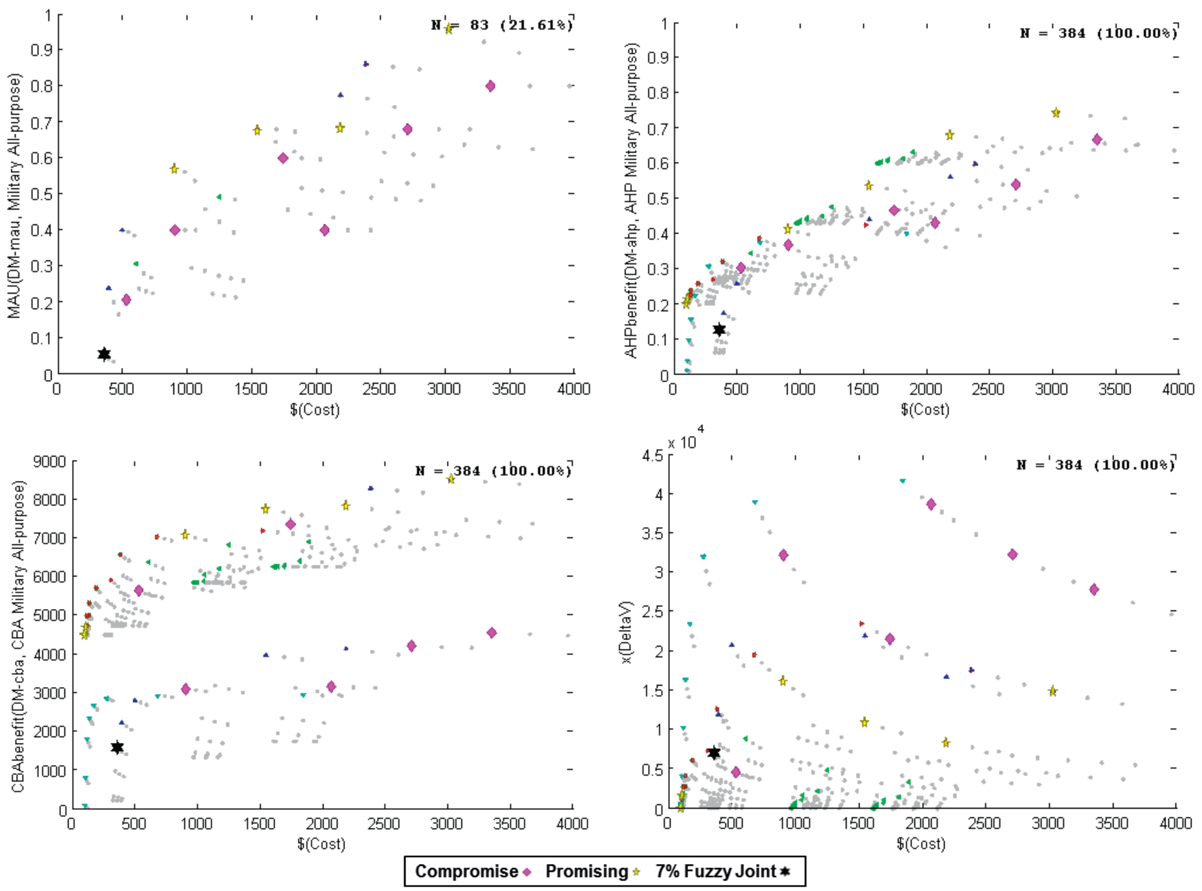


Fig. 10. Comparison of benefit versus cost tradespaces with compromise, promising, and fuzzy joint designs indicated.

Fig. 10 illustrates the four tradespaces, with the compromise, promising, and 7% fuzzy joint designs. Design 52 is the 7% fuzzy joint Pareto design and represents the most robust choice if the decision maker is unsure of which value model best captures his preferences. Interestingly this design uses electric propulsion, which was a design choice absent from the AHP and CBA Pareto sets. Appealingly, this design is in the low cost region of the tradespaces. The joint Pareto analysis identified designs that are most efficient across 3 out of 4 value models (tending to high performance, high cost solutions), as well as balanced efficiency across all 4 value models (lower performance, lower cost solution). Ultimately the foregoing value model trade analysis doesn't prescribe the "best" solution, but rather highlights several key points: 1) the choice of value model matters since it determines the attractiveness of each solution; 2) each value model will likely highlight different systems; 3) it is possible to identify systems that do well across multiple value models; 4) this type of analysis is useful if the most appropriate value model to use is uncertain or likely to change. One could theoretically wrap an optimizer around the joint Pareto analysis to identify a "best" solution; however, this would obfuscate the pedagogical aim of this paper.

4. Discussion

Much of the modeling literature tends to focus on model formulation and validation in pursuit of finding "best" solutions (e.g., optimization-based approaches)[1]. Model types include performance, cost, as well as value models. As pointed out earlier[4], there is an asymmetry when validating performance models as opposed to value models. The former could have ground truth as a basis for validation, while the latter attempts to put structure on something that may be fundamentally subjective (i.e., human interpretation). As model-centric methods proliferate, and the pursuit of robust and resilient solutions becomes strategically important, analysts and engineers need to explore more than just the accuracy and sensitivity of their model results; they must also explore the impact of model choice itself. Where ground truth might be available, model validation is possible, and the impact of model choice may be interpreted as error introduced into the data. Where ground truth may be unavailable, as may be the case for value models, understanding the impact of model choice on data could become an essential part of studies. The demonstration case for value model trading was intended to help identify key tasks and supporting infrastructure for value model trading capabilities. The case did result in the ability to use different value model formulations on a common data set. The next phase of the research will continue analyzing value model trades in this case, and will develop a more complete framework and process for conducting value model trades in general.

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